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Determinants of household fuelwood collection from mangrove plantations in coastal Bangladesh

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ABSTRACT

The Government of Bangladesh has been establishing mangrove plantations since 1960. This study analyzes results from a household survey across eight coastal villages to investigate how local rural communities utilize these resources. The predominant direct use by households is the extraction of combustible fuel. Econometric results suggest that determinants of the household decision to collect fuelwood include respondent occupation and village. Farmers are less likely to extract mangrove fuels due to the availability of substitutes such as agricultural residues, and are also less likely obtain non-mangrove fuelwood via market purchase. Collection quantities are positively correlated with degree of impoverishment, with poorer households significantly less likely to access non-mangrove fuelwood markets. These results are robust to selection bias, spatial lag dependence, and spatial error dependence, and have important policy implications for beneficiary selection for future mangrove plantations.

1. Introduction

Since 1960, the Government of Bangladesh has established coastal mangrove plantations for the purposes of shoreline stabilization and storm surge protection. The Bangladesh Forest Department undertakes and monitors plantation activities, which are a significant component of the country's adaptation response to climate change. Although felling of whole trees is prohibited, the extraction of non-main stem material (e.g., limbs, pneumatophores, and leaves) by local communities is allowed and is the predominant direct use of mangrove plantations (Chow, 2015).

Woody combustion fuel (hereafter, fuelwood) is in some of the developing world the largest output generated from forests, benefitting more of the rural poor than any other forest product (Arnold et al., 2003). Studies of fuelwood collection typically explore several factors which affect household production possibilities and demand preferences. Research from Asia (e.g., Cooke, 1998; Heltberg et al., 2000; Kohlin and Parks, 2001; Sills et al., 2003; Gundimeda and Kohlin, 2008) generally indicate that the impact of household wealth on fuelwood production is highly location-specific, and may vary even within the same region. They often find that landholding and livestock ownership, as proxies for wealth and capital, respectively, can be positively correlated with total fuelwood collection, and market expenditures, particularly in remote areas where combustible fuels are scarce (e.g., Amacher et al., 1993; Amacher et al., 1996, 1999; Chen et al., 2006). In places such as coastal Bangladesh where fishing is a major economic activity, landholding and livestock are not universally applicable metrics. Therefore, evaluation of the determinants of fuelwood collection requires localized investigation, since predictions of household behavior are difficult to extrapolate from one area to another.

This study investigates how household characteristics affect fuelwood collection from mangrove plantations in coastal Bangladesh. Empirical analysis of fuelwood scarcity has generally overlooked the very poor, who often have less access to substitutes for fuels collected from village commons (Cooke et al., 2008). Most research also ignores the landless, which this study addresses by focusing on coastal villages where households are engaged in land-intensive activities such as farming as well as non-land-intensive activities such as fishing.

The rest of the paper is organized as follows. Section 2 describes the study area, survey methodology, and summary statistics. Section 3 introduces the theoretical model which motivates the reduced form empirical model described in Section 4. Section 5 presents and interprets results from the empirical model along with robustness checks and Section 6 concludes the paper with a discussion of policy implications.

2. Study area, methodology, and summary statistics

Bangladesh (20.6–26.6°N, 88–92.6°E) has a coastal zone where 75%

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Table 1
Breakdown of administrative units included in study.

Division	District	Upazilla	Village	Sample size (households)
Barisal	Barguna	Patharghata	Padma	49
		Taltoli	Sokina	50
	Patuakhali	Kalapara	Momripara	30
	Bhola	Char Fasson	Babugonj	36
Chittagong	Chittagong	Sitakunda	Mirzanagar	40
			Saidpur	39
		Mirsarai	Gazaria	45
	Noakhali	Hatiya	Aladigram/ Kalirchar	50

of the population lives in rural communities reliant upon agro-ecosystems and natural resources (Iftekhar, 2006). Deltaic sedimentation creates new coastal formations—*chars*—where the Bangladesh Forest Department has established mangrove plantations within the districts of Patuakhali, Barisal, Bhola, Noakhali and Chittagong (Saenger and Siddiqi, 1993).

This study analyzes data on demographics, livelihoods, geospatial location, and fuelwood collection behavior from households within eight villages spanning seven upazillas (subdistricts) (Table 1): Aladigram/Kalirchar, Babugonj, Gazaria, Padma, Momripara, Mirzanagar, Sokina, and Saidpur. Aladigram and Kalirchar are officially two villages but are situated contiguously, hence this study treats them as a single village. Surveys of 340 households—approximately 10% of all households within the selected villages—were conducted in 2012 as described by Chow (2015). Each respondent, typically a representative head of household, was selected if they were willing to complete the full survey, if they were an income earner, and, if the household collected mangrove materials, personally participated in collection. The sample was otherwise random. After surveys in two villages, Padma and Sokina, were complete, the questionnaire was modified to collect additional information on other fuels: purchased fuelwood, homestead trees, livestock dung, and other agricultural residues (e.g., grass and rice straw).

Table 2 lists key summary statistics by village. Years of formal education for this cohort is low across villages, the overall average being about three years. Households number six people on average, with over a third having multiple income earners due to the presence of multiple generations of working age. A majority of respondents in each village partake in multiple income-generating activities. Nearly half of all respondents cultivate land that they either own or rent, and over a quarter work as hired farm labor at some point during the year. Over 40% of respondents engage in marine, coastal, or riparian fishing using their own equipment, but only 4% work as hired fishing labor.

Respondents usually do not keep records of their revenues and expenditures and are typically unaware of their total annual earnings. This study calculates incomes based on answers to questions related to wages, expenditures, revenues, and frequency of income-generating activities. Because of the numerous estimations and imperfect recollections involved in calculating the net revenues of any particular activity, the calculated incomes are prone to substantial error. Unadjusted, income estimations are negative for 110, or nearly a third, of respondents. Since households are unlikely to truly have negative incomes, at least for long periods of time, negative calculated incomes are converted to zero for the purposes of these analyses. This adjustment suggests that households with negative incomes operate at a subsistence level and generate little surplus, a reasonable assumption for rural households in Bangladesh. However, because no similar adjustment is implemented for possibly overestimated incomes, the following averages are likely overestimates. Considering the adjusted data, average respondent income is Tk.302,000 per year (USD3887 per year), though this varies substantially by village. Average household income, calculated based on respondents' estimates of their proportional contribution, is Tk.464,000 per year (USD5972 per year).

An alternate measure of wealth is the number of rooms in the family home, under the presumption that the wealthier the household, the greater the number of rooms. Ordinary least squares (OLS) regression between total household income and the number of rooms confirms that the two characteristics are linearly correlated (Table 3). However, the number of rooms is also correlated with household size, likely due to a greater need for living space for larger families. Larger families are also more likely to have multiple income earners, further confounding the relationship between household size, rooms, and household income. Household income, household size, the number of income earners, and the number of rooms are all correlated with each other.

Table 2
Summary statistics at village level. Standard deviations in parentheses.

	Aladigram/ Kalirchar	Babugonj	Gazaria	Mirzanagar	Momripara	Padma	Sokina	Saidpur	All
Total households (approx.)	500	300	149	280	500	650	293	NA	
Number of respondents	50	36	45	40	30	49	50	39	339
# Activities (respondent only)	2.32 (0.87)	1.89 (0.71)	1.62 (0.65)	1.58 (0.59)	1.63 (0.72)	2.22 (0.96)	1.96 (0.75)	1.67 (0.66)	1.9 (0.8)
% Respondents w/mult. jobs	84	69.4	53.3	52.5	53.3	77.6	70	56.4	65.6
% Fishers, any (own equipment)	40	75	6.7	60	33.3	34.7	76	10.3	42.1
% Boat fishers (own equipment)	26	63.9	0	50	33.3	26.5	70	5.1	34.1
% Shore fishers (own equipment)	14	13.9	6.7	10	3.3	8.2	6	5.1	8.5
% Fishers (hired labor)	8	2.8	0	2.5	0	10.2	12	0	5
% Farmers	42	33.3	84.4	0	73.3	26.5	32	87.2	46.2
% farm (hired labor)	30	27.8	28.9	22.5	16.7	26.5	26	35.9	27.1
Mean age of respondent	39.6 (10.43)	38.44 (11.75)	45.84 (14.34)	44.08 (12.75)	39.8 (16.52)	42.39 (15.44)	34.82 (9.52)	37.33 (10.85)	40.31 (13.09)
Mean years of education	1.26 (2.42)	2.89 (3.22)	1.8 (2.56)	2.23 (2.6)	3.3 (2.68)	4.22 (3.6)	3.98 (2.65)	4.05 (3.56)	2.96 (3.11)
Mean household size	6.4 (2.09)	5.14 (1.51)	5.53 (1.27)	7.05 (2.93)	4.87 (1.63)	5.18 (1.86)	4.98 (1.39)	5.51 (1.93)	5.61 (2)
Mean # rooms	2.62 (1.19)	2.5 (1.13)	3.44 (1.8)	3.58 (1.3)	2.5 (0.94)	2.34 (1.05)	2.06 (1.1)	3 (1.1)	2.75 (1.33)
Mean persons per room	2.79 (1.16)	2.53 (1.37)	1.89 (0.74)	2.07 (0.68)	2.21 (1.02)	2.56 (1.27)	3.13 (1.75)	2.07 (0.92)	2.44 (1.24)
Mean respondent income (1000Tk/yr)	214 (745)	85 (185)	80 (99)	1253 (2130)	70 (93)	310 (789)	229 (808)	169 (232)	302 (961)
mean household income (1000 Tk/yr)	242 (746)	100 (203)	126 (186)	2395 (4717)	75 (100)	379 (861)	235 (807)	208 (241)	464 (1834)
Mean fuelwood, collectors only (kg/yr/HH)	4303 (6519)	2076 (3579)	2067 (1484)	464 (430)	1592 (2361)	3687 (4169)	3847 (5059)	2143 (1523)	3007 (4397)
Mean fuelwood, all (kg/yr/HH)	40.44 (64)	19.61 (35.08)	12.86 (15.43)	0.348 (1.57)	13.27 (22.31)	26.33 (38.91)	30.78 (47.73)	10.99 (15.29)	20.52 (38.91)

Table 3
Matrix of Pearson's linear correlation coefficients for total household income, household size, number of income earners, number of rooms, and persons per room. Coefficients for OLS regression are all significant at P = 0.01 level except where indicated. *P < 0.1. **P > 0.1. ***P < 0.05.

	Own income	HH income	HH size	No. of earners	No. of rooms
HH income	0.88				
HH size	0.23	0.33			
No. of earners	0.1*	0.24	0.48		
No. of rooms	0.20	0.29	0.44	0.48	
Persons per room	−0.05**	−0.06**	0.18	−0.11***	−0.66

This study therefore employs an alternate measure of wealth: the ratio of household size to number of rooms. A smaller ratio, with fewer people per room, suggests greater wealth, whereas a larger ratio, with more people inhabiting a smaller space, suggests less wealth. As an indicator of household material resources (Galobardes et al., 2006), this measure has the advantage of being less subject to error-prone recollections of numerous expenditures and revenues, and is calculated from two values, the number of household members and the number of rooms, that are easily recalled by the respondent. Moreover, the persons-to-rooms ratio may better reflect long-term wealth, since respondents answering questions about expenditures and revenues often recall best the most recent year. On average, 2.44 persons reside per room (Table 2). Separate analyses of Household Income Expenditure Survey data (BBS, 2000, 2007, 2011) from coastal households also indicate that persons per room is significantly negatively correlated with the total value of household assets (Chow, unpublished), hence greater persons per room is used here as a proxy for lower socioeconomic position.

Although an imperfect indicator, persons per room has the advantage of being a universal metric of socioeconomic position, whereas other commonly used indicators (reviewed by Vyas and Kumaranayake, 2006) have limited applicability in coastal Bangladesh. Since this study focuses entirely on relatively poor villages, there is little variation in water supply and sanitation facilities, as almost all households rely on either wells or surface sources for water, and toilets to open spaces. These remote areas largely lack electrification, therefore durable assets like radios, televisions, and refrigerators are rare. Ownership of other types of assets, such as cattle, land, and boats, depend on the chosen income earning activities of the household. Among farmers, 15% own cultivated land and 15% own cattle, compared to 3% and 5% of fishing households. Conversely, 81% of fishing households own a boat, compared to 19% of farmers. Even indicators such as some types of home construction material are related more to local availability rather than wealth. For example, leafy thatch material is mainly used in villages where its source, the mangrove palm *Nypa fruticans*, grows in sufficient quantities for there to be a local market (Chow, 2015).

With these limitations in mind, this study constructs an alternate index of socioeconomic status, via principle components analysis (PCA) of variables including persons per room, as well as indicators for asset ownership and home construction materials (Table 4). As a robustness check against results derived from the persons per room metric alone, the first principle component is used as an alternate measure of the socioeconomic condition of the household (following Vyas and Kumaranayake, 2006).

The vast majority of the surveyed household representatives are male because seldom do women engage in income-generating activities outside of the home. Men are also often responsible for fuelwood collection, particularly when the capital employed is associated with the primary occupation (e.g., boats used by fishermen). Due to restrictions against taking main stems from government plantations, no respondent admits to doing so. This analysis considers only woody material, such as branches and pneumatophores, and not non-woody material such as leaves. Leaves are omitted here because only eight respondents, and only from Mirzanagar, collect them for combustible fuel, and because the difference in energy density between woody and leafy materials complicates comparisons by mass. Among collecting households only, the average fuelwood extraction is over three thousand kg per year.

Table 4
Results from principle components analysis.

Variable	Mean	Std. dev.	Factor score
Demographic and housing			
Persons per room	2.44	1.24	0.3702
Number of rooms	2.75	1.33	−0.3729
Owned assets (indicator)			
House owner	0.97	0.18	−0.0682
House land owner	0.66	0.47	−0.1606
Farm land owner	0.08	0.27	−0.1513
Boat owner	0.34	0.47	0.1239
Cattle owner	0.11	0.31	−0.0252
Wall material (indicator)			
Bamboo	0.32	0.47	−0.0369
Brick	0.03	0.16	−0.0699
Cement	0.003	0.05	−0.0035
Wood	0.1	0.3	−0.0283
Leaf (thatch)	0.05	0.22	0.3168
Soil	0.02	0.13	0.0888
Plastic	0.003	0.05	−0.0056
Straw	0.03	0.18	0.2136
Tin	0.44	0.5	−0.167
Roof material (indicator)			
Bamboo	0.003	0.05	0.1299
Brick	0.003	0.05	0.0158
Cement	0.003	0.05	−0.0214
Leaf (thatch)	0.04	0.18	0.3457
Straw	0.06	0.24	0.3171
Tin	0.9	0.3	−0.4776

3. Theoretical model

Motivating the reduced form empirical strategy is a stylized generic model, modified from Sills et al. (2003), of a coastal rural household living near the forest Eq. (1). The household engages in agriculture (A), fishing (F), and fuelwood collection (W). I assume complete markets for agricultural and fishing products but incomplete markets for coastal plantation fuelwood and labor, since respondents rarely reported buying or selling mangrove fuelwood, and because labor opportunities are limited, particularly for women (Kabeer, 1991). The amounts of labor and leisure available are constrained by total household person-hours (T), and cash expenditures on market goods (M)[2] are constrained by the market value of the agricultural and fishing output plus any exogenous income (I). The household seeks to maximize a single utility function which incorporates consumptions of agricultural goods (A_H), fishing goods (F_H), market goods (M_H), fuelwood (W_H), and home time (T_H), which includes leisure and household chores. Household utility is conditioned on preferences (Φ).

$$\max\ \mathrm{U}(\mathrm{AH}, \mathrm{FH}, \mathrm{MH}, \mathrm{WH}, \mathrm{TH}; \Phi) \tag{1}$$

s.t.

(1) $T \geq T_H + T_A + T_F + T_W$
(2) $A = a(T_A, M_A; \Psi)$
(3) $F = f(T_F, M_F; \Psi)$
(4) $W = w(T_W, M_W; B, H, \Psi)$
(5) $W \geq W_H$

[2] Technically, P_M and M ought to represent vectors of market prices and goods, but for simplicity's sake and without loss of generality they are collapsed into scalars here.

(6) $P_A(A - A_H) + P_F(F - F_H) + I \geq P_M(M_H + M_A + M_F + M_W)$

The choice variables are T_H, T_A, T_F, T_W, M_H, M_A, M_F, M_W, A_H, F_H, and W_H. The constraints apply to (1) household time, (2) agricultural production, (3) fishing production, (4) plantation fuelwood production, (5) plantation fuelwood consumption, and (6) cash budget. Agricultural production is a function (a) of household time allocated to agriculture (T_A) and inputs purchased in markets (M_A) conditioned on fixed production endowments and technology (Ψ). Similarly, fishing catch production is a function (f) of household time allocated to fishing (T_F) and a different set of market-bought inputs (M_F), again conditioned on fixed characteristics (Ψ). Fuelwood production from mangrove plantations is a function (w) of time allocated to collection (T_W) and market-bought inputs (M_W), conditioned by its biophysical state (B), household knowledge of the forest (H), and fixed endowments (Ψ). Combining constraints (4) and (5) yields five constraints and a Lagrangian function with five shadow values (α, β, γ, δ, ε) Eq. (2):

$$\begin{aligned} L = {} & U(A_H, F_H, M_H, W, T_H; \Phi) + \alpha(T-(T_H + T_A + T_F + T_W)) \\ & + \beta(a(T_A, M_A; \Psi)-A) + \gamma(f(T_F, M_F; \Psi)-F) \\ & + \delta(w(T_W, M_W; B, H, \Psi)-W_H) \\ & + \varepsilon((P_A(A-A_H) + P_F(F-F_H) + I)-P_M(M_H + M_A + M_F + M_W)) \end{aligned} \tag{2}$$

The first-order conditions with respect to the choice variables directly related to fuelwood production and consumption are

$$\frac{\partial L}{\partial T_W} = -\alpha + \delta\frac{\partial w}{\partial T_W} = 0 \tag{3}$$

$$\frac{\partial L}{\partial W_H} = \frac{\partial U}{\partial W_H} - \delta = 0$$

Therefore,

$$\alpha = \delta\frac{\partial w}{\partial T_W} = \frac{\partial U}{\partial W_H}\frac{\partial w}{\partial T_W} \tag{4}$$

Eq. (4) indicates that utility-maximizing households allocate their time such that the shadow value of time (α) is equal to the marginal utility associated with spending more time collecting fuelwood. Other FOCs suggest that the shadow value of time depends also on the parameters of the production functions:

$$\alpha = \beta\frac{\partial a}{\partial T_A} = \gamma\frac{\partial f}{\partial T_F} \tag{5}$$

Also, the marginal utilities of increased agricultural and fishing production (β and γ) are related to the shadow value of income (ε):

$$\varepsilon = \beta\frac{1}{P_M}\frac{\partial a}{\partial M_A} = \gamma\frac{1}{P_M}\frac{\partial f}{\partial M_F} \tag{6}$$

Consequently, the shadow values all depend on the full set of exogenous variables, including prices and exogenous income. Therefore, fuelwood collection, consumption, and the derived demand for labor are also functions of all exogenous variables. Household production and consumption decisions are termed non-separable whenever the shadow value of at least one production-consumption good is determined endogenously by the interaction between household demand and supply rather than taken exogenously from the market price (Löfgren and Robinson, 1999). This occurs when key markets are incomplete, such as for coastal plantation fuelwood and labor in this stylized example.

4. Empirical model

Due to non-separability of household production and consumption, collection of fuelwood is a function of all exogenous factors $h(\Phi, \Psi, B, H, I, P)$. This study estimates reduced form empirical models with probit and OLS regressions in two stages. In the first stage, a binary variable representing the decision whether to collect plantation fuelwood (1 = yes, 0 = no) is the dependent variable in a probit regression with education, respondent age, household impoverishment (i.e., persons per room), and a set of occupation and location fixed effects. The second stage quantitative decision model considers only those households that collect from the plantations and uses OLS, with and without a Heckman correction, to regress total annual plantation fuelwood extraction (kg) onto the variables above as well as a measure of collection ability.

In studies of fuelwood extraction, exogenous factors are often represented by household demographics, wealth or assets, income sources, availability of substitutes, and regional resource and market characteristics (reviewed in Sills et al., 2003). Education and age reflect production possibilities and preferences. Occupation fixed effects (for farming, farm labor, boat fishing, shore fishing, and fishing labor) can reflect both wealth and availability of substitutes. For example, a farmer who owns land and livestock is wealthier than an individual who is primarily a shore fisherman, and the farmer may also have greater access to home tree lots, cattle dung, and agricultural residues. “Labor”, either for farming or fishing, suggests employment as hired help, whereas “farming” and “fishing” indicate self-employment. “Boat fishing” refers to maritime fishermen who use boats to travel to their fishing sites and cast their nets, whereas “shore fishing” refers to fishermen who walk to their sites and cast their nets from shores or shallow waters. These occupational categories are not mutually exclusive or exhaustive, but nonetheless represent the major income-generating activities among villagers, who individually may engage in multiple activities over the course of a year. The characteristics recorded in this study are those of the survey respondent only, rather than the household as a whole, making them imperfect proxies of household-level production possibilities and preferences.

Location fixed effects—by district, upazilla, or village depending on the specification—account for local and regional market characteristics (e.g., wages), as well as the biophysical condition of the local plantation resource. Among the location fixed effects, Padma village—in Patharghata upazilla and Barguna district—was the first village surveyed, and is arbitrarily chosen as the index against which others are compared, hence no coefficients for these locations appear in the model specifications.

Although household size and the number of income earners also reflect production possibilities and fuelwood demand, these characteristics are linearly correlated with total household income (Table 3). Specifications that include these variables yield coefficients that are not significant, thus they are not included in the empirical model. This analysis employs persons per room as a measure of lower socioeconomic status, and poorer households are expected to collect more fuelwood from the plantations. The socioeconomic index derived from PCA, described in Section 2, is used as a robustness check for results based on the persons per room metric alone. Similar to persons per room, higher values indicate a greater degree of impoverishment.

I estimate reduced form models both for the binary fuelwood collection decision and for quantities collected. Since a large proportion of respondents choose not to collect plantation fuelwood, I use the generalized Heckman approach to explore potential selectivity bias. This method employs a first-stage probit model of the binary collection decision to predict the extraction probability, a transformation of which is included in the second stage OLS as an additional explanatory variable (reviewed by Lee, 2001). I evaluate sample selectivity by testing against the null hypothesis that the coefficient on the inverse Mills ratio, λ, is zero.

I employ two different specifications of collection efficiency in the second stage: one the ratio of quantity extracted to total excursion time; and the other a similar ratio, but distinguishing between quantity per

unit of travel time and quantity per unit of collection time. The latter specification also includes an indicator variable to distinguish between respondents that collect on single-day trips and those that collect on trips spanning two days or more. The collection quantities of the dependent variable are used to calculate these efficiency measures, so these variables are inherently endogenous. However, they are included as a rough measure of ability in order to control for this characteristic.

In regression models of spatially explicit phenomena, spatial correlation may occur due to spillovers among the dependent variables, known as spatial lag dependence, or due to spillovers among the error terms, or spatial error dependence. Within the context of this study, spatial lag dependence could occur if households' decisions whether to collect fuelwood influence their neighbors' decisions. For example, if members of neighboring households tend to accompany each other on collection trips, there may be positive spillovers on the collection decision. On the other hand, if households tend to share or trade their fuelwood with neighbors, there may be negative spillovers on both the collection decision and the quantities collected by recipient households. Spatial error dependence occurs when unobserved drivers of fuelwood collection are correlated across space. Correlation due to either spatial lag dependence and spatial error dependence generates heteroskedastic errors and traditional regression estimators are inefficient because they assume independent errors. As a robustness check for spatial lag dependence in the first stage, I use LeSage and Pace's (2009) Bayesian spatial autoregressive (SAR) model and spatial error model (SEM) for probit. To test for spatial correlation in the second stage, I estimate LeSage and Pace's spatial autoregressive models and spatial error models for OLS.

I iterate all spatial models with continuity weights matrices generated according to three methods: 5 nearest neighbors, 10 nearest neighbors, and Delaunay triangulation. All "neighbors" (i.e., the households that influence i) are assumed to have the same effect on i. The Delaunay triangulation method defines the neighbors of household i as those that can be connected to i with a set of triangles such that i is at one corner, neighbors are at the other two corners, and the circumcircle drawn through all three corners do not contain any other sample plots.

Finally, to further explore the rationale underlying mangrove fuelwood extraction choices, I estimate binary choice probit models for the decision to obtain substitute combustible fuels from each of the following sources: marketed fuelwood from non-mangrove forests, trees on home plots, livestock dung, and other agricultural residues. Each binary choice (yes = 1, no = 0) is the dependent variable for a probit regression, with respondent age, education, persons per room, and occupational fixed effects as explanatory variables. In cases where an occupational fixed effect is a perfect predictor of the dependent variable, that variable is dropped from the specification. While the probit model for marketed fuelwood includes data from all respondents, the models for other substitutes exclude Padma and Sokina because the questionnaire was modified to include this information after surveys in these villages were completed.

5. Empirical model results and interpretation

5.1. Binary collection decision model

The decision to collect (yes = 1, no = 0) is regressed on age, education, and persons per room, with and without occupation and location fixed effects, in nine specifications of the first stage probit model (Table 5). Distance from home to plantation was also evaluated (not shown), but was found to be insignificant in all cases—possibly due to insufficient variation within the geographically small villages—and hence dropped from the models. Persons per room also is not significant in any binary decision model for fuelwood collection.

Age and years of education of the respondent are significant at the P = 0.05 level, but not consistently across specifications. Coefficients for one or both variables tend not to be significant in models which include both location and occupation fixed effects (e.g., Table 5, model 7), but are significant in specifications either with just the village fixed effects (model 6), or with occupation and location fixed effects defined at higher levels of aggregation (i.e., district, model 1). The non-significance of coefficients in models with greater inclusion of fixed effects is likely due to insufficient within-group variation.

Coefficients for age and years of education are consistently negative across all models, indicating that households with older or better-educated primary income earners are less likely to collect fuelwood from the mangroves. Respondents may be less inclined to carry heavy fuelwood loads as they age and therefore seek alternatives, unless a younger member of the household is responsible for obtaining household fuels. Education is significant in only a few specifications but with a consistently negative coefficient. Thus, respondents with more education are less likely to collect fuelwood, possibly reflecting higher opportunity costs of time.

Among the occupational variables, only the farming-related fixed effects are significant for any model specification. The coefficient for the farm labor fixed effect is consistently positive but also weakly to moderately significant only for specifications without village-level fixed effects. In contrast, the farming fixed effect is consistently negative and highly significant for specifications which include village-level fixed effects. These results suggest that agricultural laborers are more likely to utilize the mangrove plantations for fuelwood while farmers who cultivate their own or rented lands are less likely to do so.

Notably, Mirzanagar is the only village with a consistently significantly negative coefficient, which indicates that its residents are the least likely to collect mangrove fuelwood. This outcome may be due to the relative youth of the plantations here, which were established in the early 1990s whereas the other plantations were established in the 1970s and 1980s. Mirzanagar is also the village closest to a major city, Chittagong, as well as to a major road, giving its residents greater access to marketed fuelwoods from inland forests. All respondents from Mirzanagar report purchasing fuelwood, compared to only 0–25% in other villages. Thus the lower propensity to collect mangrove fuelwood may be due to both the youth of the local plantation, with smaller trees and less collectable material, and proximity to markets.

In addition to specifications with and without all occupation and location fixed effects, other models are estimated that eliminate non-significant dummy variables in a stepwise fashion. Hence, a final model was estimated with only the significant fixed effects for farming and four villages (Table 5, Model 8). Substituting the persons per room variable with the socioeconomic index does not dramatically alter the results (Model 9). Bayesian SAR and SEM probit analyses using the variables in Model 8 indicate that these results are robust to both spatial lag dependence and spatially correlated errors (Appendix).

5.2. Collection quantity model

Selection models with differing specifications are used in the Heckman analyses (Table 6): 1) age, education, and persons per room with only village fixed effects; 2) the full model with both occupational and village fixed effects; and 3) binary choice model 8 described in Section 5.1. Age, education, and occupation, and village fixed effects are not included in the collection stage, in order to retain exclusion restrictions which mitigate collinearity of λ. Collection efficiency is consistently positively significant for all specifications, but models which include both kg/travel time and kg/collection time reveal that only the latter is significant. Hence efficiency in collection itself, rather than in transporting it from the plantation back to the residence, is the attribute relevant to quantities extracted. Distance to mangroves was not significant in any specification and not included in the reported empirical models. Persons per room is consistently positively and significantly correlated with collection quantities at the P = .05 level, which suggests that poorer respondents collect more fuelwood.

Table 5
Parameter estimates for binary choice probit regression of fuelwood collection (yes = 1, no = 0) onto explanatory variables. Standard errors in parentheses. *P < 0.10. **P < 0.05. ***P < 0.01.

Model #	1	2	3	4	5	6	7	8	9
Fixed Effects (FE)	District, Occupation	Upazilla	Upazilla, Occupation	Village	Village, Occupation	Village	Village, Occupation	Village, Occupation	Village, Occupation
Age of respondent	−0.013 (0.006)**	−0.015 (0.006)**	−0.014 (0.007)**	−0.013 (0.007)**	−0.009 (0.007)	−0.009 (0.007)	−0.008 (0.007)	−0.009 (0.007)	−0.008 (0.007)
Years of education	−0.053 (0.028)*	−0.041 (0.027)	−0.033 (0.029)	−0.058 (0.028)**	−0.033 (0.030)	−0.035 (0.028)	−0.035 (0.028)	−0.040 (0.028)	−0.039 (0.028)
Persons per room	0.020 (0.074)	0.032 (0.073)	0.013 (0.77)	0.023 (0.074)	−0.040 (0.080)	−0.035 (0.077)	−0.032 (0.077)	−0.025 (0.075)	
Socioeconomic index									0.022 (0.093)
Boat fishing FE	−0.043 (0.20)		0.032 (0.22)		0.19 (0.24)	0.23 (0.21)	0.27 (0.21)		
Shore fishing FE	−0.34 (0.31)		−0.35 (0.31)		−0.32 (0.33)	−0.32 (0.33)	−0.29 (0.33)		
Fish labor FE	0.55 (0.46)		0.58 (0.48)		0.62 (0.53)	0.64 (0.52)	0.68 (0.52)		
Farming FE	0.15 (0.19)		−0.041 (0.20)		−0.62 (0.23)***	−0.59 (0.22)***	−0.64 (0.22)***	−0.75 (0.20)***	−0.71 (0.21)***
Farm labor FE	0.40 (0.20)**		0.42 (0.20)**		0.26 (0.21)	0.26 (0.21)	0.23 (0.21)		
Bhola FE	0.93 (0.37)**								
Chittagong FE	−0.96 (0.21)***								
Noakhali FE	0.79(0.34)**								
Patuakhali FE	0.28 (0.32)								
Char Fasson FE		0.98 (0.40)**	1.02 (0.40)**						
Hatiya FE		0.87 (0.35)**	0.94 (0.36)***						
Kalapara FE		0.37 (0.34)	0.46 (0.35)						
Mirsarai FE		−0.25 (0.28)	−0.19 (0.31)						
Sitakunda FE		−1.16 (0.25)***	−1.15 (0.26)***						
Taltoli FE		0.17 (0.29)	0.15 (0.31)						
Aladigram FE				0.83 (0.35)**	1.08 (0.38)***	0.98 (0.32)***	1.05 (0.32)***	1.00 (0.31)***	1.00 (0.32)***
Babugonj FE				0.98 (0.40)**	1.09 (0.42) **	0.99 (0.38)***	1.05 (0.38)***	1.05 (0.38)***	1.04 (0.37)***
Gazaria FE				−0.31 (0.29)	0.11 (0.32)				
Mirzanagar FE				−2.10 (0.36)***	−2.28 (0.38)***	−2.36 (0.35)***	−2.34 (0.35)***	−2.38 (0.34)***	−2.33 (0.35)***
Momripara FE				0.34 (0.34)	0.67 (0.36)*	0.58 (0.30)*	0.65 (0.29)**	0.62 (0.29)**	0.61 (0.29)**
Sokina FE				0.18 (0.29)	0.17 (0.32)				
Saidpur FE				−0.58 (0.28)**	−0.20 (0.32)	−0.29 (0.25)			
constant	1.19 (0.46)***	1.26 (0.44)***	1.12 (0.47)**	1.30 (0.45)***	1.23 (0.50)**	1.31 (0.46)**	1.20 (0.45)**	1.44 (0.41)***	1.36 (0.33)***
pseudo R^2	0.2187	0.2367	0.2515	0.2846	0.3167	0.316	0.3129	0.3007	0.3006

Table 6
Parameter estimates for Heckman analyses of various specifications of the collection model and selection model. Standard errors in parentheses. *P < 0.10. **P < 0.05. ***P < 0.01.

Model #	1	2	3	4	5	6
FW Collection Model						
kg/h total time	10.20 (3.34)***	10.09 (3.34)***	10.07 (3.30)			
kg/h travel time				−0.41 (0.80)	−0.41 (0.80)	−0.43 (0.80)
kg/h collection time				7.98 (2.13)***	7.94 (2.13)***	8.03 (2.12)***
Overnight FE	470.94 (1966.38)	433.09 (1964.12)	501.38 (1959.57)	1892.49 (2131.78)	1809.22 (2130.99)	1876.98 (2125.90)
Persons per room	621.24 (224.46)***	610.67 (223.25)***	581.22 (221.71)***	593.15 (220.66)***	577.42 (219.45)***	569.45 (219.22)***
Constant	903.06 (838.54)	1009.02 (805.61)	1270.88 (729.84)*	1007.42 (784.89)	1155.45 (738.57)	1219.78 (722.37)*
Selection Model						
Age of respondent	−0.013 (0.0066)**	−0.0086 (0.0070)	−0.0088 (0.0065)	−0.014 (0.0066)**	−0.0087 (0.0069)	−0.0089 (0.0065)
Years of education	−0.058 (0.028)**	−0.033 (0.030)	−0.036 (0.028)	−0.057 (0.028)**	−0.030 (0.030)	−0.036 (0.028)
Persons per room	0.023 (0.074)	−0.040 (0.080)	−0.027 (0.075)	0.019 (0.074)	−0.044 (0.080)	−0.033 (0.076)
Boat fishing FE		0.19 (0.24)			0.22 (0.24)	
Shore fishing FE		−0.32 (0.33)			−0.33 (0.33)	
Fish labor FE		0.62 (0.53)			0.53 (0.54)	
Farming FE		−0.62 (0.23)***	−0.78 (0.20)***		−0.66 (0.24)***	−0.78 (0.20)***
Farm labor FE		0.26 (0.21)			0.23 (0.21)	
Aladigram FE	0.83 (0.35)**	1.08 (0.38)***	1.06 (0.32)***	0.89 (0.37)**	1.17 (0.38)***	1.08 (0.32)***
Babugonj FE	0.98 (0.40)**	1.09 (0.42)**	0.98 (0.39)**	0.91 (0.42)**	1.00 (0.43)**	0.95 (0.39)**
Gozaria FE	−0.31 (0.29)	0.11 (0.32)		−0.31 (0.28)	0.14 (0.32)	
Mirzanagar FE	−2.10 (0.36)***	−2.28 (0.38)***	−2.39 (0.34)***	−2.10 (0.36)***	−2.30 (0.38)***	−2.39 (0.34)***
Momripara FE	0.34 (0.34)	0.67 (0.36)*	0.59 (0.29)**	0.33 (0.34)	0.66 (0.36)*	0.60 (0.29)**
Sokina FE	0.18 (0.29)	0.17 (0.32)		0.17 (0.29)	0.16 (0.32)	
Saidpur FE	−0.58 (0.28)**	−0.20 (0.32)		−0.58 (0.28)**	−0.17 (0.32)	
Constant	1.30 (0.45)***	1.23 (0.50)**	1.46 (0.41)***	1.32 (0.45)***	1.25 (0.50)**	1.48 (0.41)***
λ	−331.05 (1012.47)	−550.36 (955.00)	−1058.35 (700.41)	−639.23 (885.74)	−958.71 (763.18)	−1077.99 (698.39)

Table 7
Parameter estimates for OLS regression of total fuelwood collected (kg) onto explanatory variables. Standard errors in parentheses. *P < 0.10. **P < 0.05. ***P < 0.01.

Model #	1	2	3	4	5	6	7	8
Fixed Effects (FE)	District, Occupation	Upazilla	Upazilla, Occupation	Village	Village, Occupation	Village, Occupation	Village, Occupation	Village, Occupation
Kg/h collection time	11.22 (3.34)***	11.49 (3.05)***	11.23 (3.34)***	11.48 (3.05)***	11.19 (3.37)***	10.67 (2.96)***	11.01 (2.77)***	11.05 (2.81)***
Age of respondent	−17.40 (26.41)	−22.36 (25.34)	−18.57 (26.96)	−23.02 (25.45)	−18.74 (27.01)	−16.08 (24.71)	−20.67 (24.46)	−17.97 (24.34)
Years of education	36.21 (74.33)	33.24 (65.92)	42.74 (75.21)	31.85 (65.90)	42.22 (75.13)	38.07 (65.94)	24.84 (64.96)	26.57 (66.59)
Persons per room	452.0 (223.4)**	533.8 (221.2)**	456.8 (223.2)**	527.0 (222.5)**	435.7 (225.7)*	426.3 (215.7)**	514.4 (213.7)**	
Socioeconomic index								604.6 (264.4)**
Boat fishing FE	−362.7 (675.4)		−299.1 (683.4)		−288.9 (682.3)			
Shore fishing FE	−441.9 (956.8)		−393.3 (965.7)		−412.1 (959.1)			
Fish labor FE	−1426.1 (817.2)*		−1403.6 (820.2)*		−1456.5 (828.8)*	−1354.7 (637.5)**	−1072.0 (538.7)**	−1169.2 (560.9)**
Farming FE	−954.6 (561.8)*		−944.5 (587.6)		−1085.4 (613.5)*	−755.6 (546.9)		
Farm labor FE	−135.7 (661.3)		−117.5 (664.4)		−195.4 (674.5)			
Char Fasson FE		−2681.5 (812.0)***	−2459.3 (872.8)***					
Hatiya FE		1984.3 (1236.3)	2223.6 (1357.8)					
Kalapara FE		−492.0 (972.5)	−173.8 (1113.7)					
Mirsarai FE		317.8 (888.6)	655.0 (1047.4)					
Sitakunda FE		9.05 (904.7)	268.9 (1020.8)					
Taltoli FE		−547.5 (985.6)	−247.0 (1019.9)					
Aladigram FE				1979.4 (1239.4)	2263.8 (1362.4)*	2113.4 (934.2)**	2125.4 (941.3)**	2156.4 (953.6)**
Babugonj FE				−2685.7 (813.8)***	−2438.6 (872.3)***	−2545.2 (530.2)***	−2486.7 (518.5)***	−2686.4 (551.5)***
Gazaria FE				310.2 (891.0)	737.2 (1051.9)			
Mirzanagar FE				−1115.8 (927.8)	−1628.2 (1105.4)			
Momripara FE				−499.4 (975.8)	−119.1 (1117.3)			
Sokina FE				−549.2 (987.8)	−222.8 (1020.5)			
Saidpur FE				167.4 (910.4)	631.1 (1031.4)			
Constant	1777.3 (1579.4)	1365.3 (1506.8)	1865.3 (1725.2)	1418.2 (1515.2)	1980.9 (1736.8)	1729.6 (1115.1)	1324.2 (1069.0)	2895.5 (1163.9)
R^2	0.2015	0.1909	0.2021	0.1919	0.2048	0.1969	0.1911	0.1866
White's test stat	76.16 (p = 0.74)	30.44 (p = 0.94)	79.52 (p = 0.96)	30.49 (p = 0.97)	79.81 (p = 0.97)	43.95 (p = 0.27)	31.95 (p = 0.42)	30.92 (p = 0.47)
BP-CW test stat	125.48 (p- = 0.00)	97.11 (p = 0.00)	125.09 (p = 0.00)	97.01 (p = 0.00)	127.10 (p = 0.00)	120.62 (p = 0.00)	104.35 (p = 0.00)	106.00 (p = 0.00)

The coefficient on λ is not significant in any specification, which indicates that there is no selection bias in the collection quantity model. Therefore, the reduced form OLS model of extraction quantities can omit households who do not collect without having to compensate for selection bias. This also allows the inclusion of age, education, occupation, and location fixed effects into collection model, since collinearity of λ is no longer a concern (Table 7). Although the White's tests do not suggest heteroskedastic errors, Breusch-Pagan/Cook-Weisberg Tests suggest the opposite. With robust standard errors to compensate for any potential heteroskedasticity, coefficients for persons per room are positive and significant at the P = .05 level in nearly all specifications. Stepwise elimination of non-significant fixed effects results in a model (number 7) with fixed effects for fishing labor and for Aladigram/Kalirchar and Babugonj. The coefficient for the fishing labor fixed effect is weakly to moderately significantly negative in most specifications, though this result is not robust in models that account for spatial correlation (Appendix). Again, using the PCA-derived socioeconomic index instead of persons per room in the model does not radically change the results (Model 8, Table 7). Estimation of the SAR and SEM models, using Model 7 from Table 7, suggests the absence of spatial correlation in collection quantities (Appendix).

These results suggest that there is an effect of impoverishment on mangrove fuelwood collection even when accounting for collection efficiency and occupation and location fixed effects. In these specifications, the coefficients for persons per room are consistently positive, suggesting as expected that poorer households collect more fuelwood, possibly due to lower opportunity costs of time, but also possibly due to cash constraints which limit poorer households' ability to purchase marketed fuelwood. The persons per room coefficient is significant in all specifications except for the model including both village and occupation fixed effects. In this case, given the relatively small sample size, including so many fixed effects may leave insufficient within-group variation to demonstrate a significant correlation.

The robustness check substituting the PCA-derived socioeconomic index for persons per room confirms these results. This outcome is unsurprising, since persons per room is included among the variables used in the PCA and has relatively high variance and factor score compared to other variables. However, these results should be considered in light of potential error due to imperfect recollection. Since over 75% of the respondents were farmers or fishermen who deal with weight metrics routinely, they presumably possess a fair sense of quantities expressed as units of mass. Collecting fuelwood is legal and the data revealed no unrealistically large collections, thus there is little to suggest that answers were deceptive. Imperfect recollections may widen the errors of parameter estimates, but there is little reason to believe that they would bias the results in any particular direction.

5.3. Fuelwood substitute choice

The results of the probit estimations modeling the decision to utilize purchased non-mangrove fuelwood, home tree lots, livestock dung, and other agricultural residues are reported in Table 8. Respondent age and education are not significant regressors in these models, since obtaining these materials is presumably easier and faster than fuelwood

Table 8
Probit results for binary choice models of fuel substitute usage. "No users" suggests that variable is a perfect predictor of the substitute choice and is therefore dropped from the model. *P < 0.10. **P < 0.05. ***P < 0.01. A) Models using persons per room. B) Models using PCA-derived socioeconomic index.

A)

	Purchased Fuelwood	Home Trees	Livestock Dung	Other Residual
Age	0.0022 (0.0064)	0.0034 (0.0063)	0.00030 (0.0074)	0.0046 (0.0082)
Education	−0.0055 (0.026)	−0.027 (0.026)	−0.055 (0.030)	−0.0037 (0.033)
Persons per room	−0.19 (0.071)***	−0.084 (0.075)	−0.078 (0.10)	−0.18 (0.12)
Boat fishing	−0.43 (0.19)**	−0.53 (0.19)	−1.22 (0.31)***	−0.56 (0.29)*
Shore fishing	−0.24 (0.29)	−0.18 (0.29)	−0.60 (0.38)	no users
Fishing labor	−0.35 (0.38)	−0.13 (0.41)	no users	no users
Farming	−0.87 (0.19)***	0.94 (0.18)***	1.36 (0.24)***	0.63 (0.25)**
Farm labor	−0.27 (0.20)	0.11 (0.19)	0.55 (0.23)**	−0.21 (0.27)
Constant	0.24 (0.39)	−0.82 (0.40)**	−1.28 (0.48)***	−1.35 (0.54)**

B)

	Purchased Fuelwood	Home Trees	Livestock Dung	Other Residual
Age	−0.0021 (0.0067)	0.0027 (0.0064)	−0.0015 (0.0076)	0.0035 (0.0088)
Education	−0.0061 (0.027)	−0.027 (0.026)	−0.057 (0.030)*	−0.0094 (0.034)
Socioeconomic index	−0.38 (0.090)***	−0.10 (0.088)	−0.15 (0.11)	−0.22 (0.13)*
Boat fishing	−0.40 (0.19)**	−0.52 (0.19)	−1.19 (0.31)***	−0.62 (0.30)**
Shore fishing	−0.20 (0.30)	−0.16 (0.29)	−0.60 (0.38)	no users
Fishing labor	−0.26 (0.38)	−0.10 (0.41)	no users	no users
Farming	−0.96 (0.19)***	0.92 (0.18)***	1.27 (0.25)***	0.52 (0.27)*
Farm labor	−0.20 (0.20)	0.12 (0.19)	0.54 (0.23)**	−0.16 (0.29)
Constant	−0.34 (0.34)	−1.08 (0.34)**	−1.43 (0.41)***	−1.62 (0.48)**

collection, and could be equally done by any member of the household. Households engaged in maritime ("boat") fishing are significantly less likely to utilize dung. Only seven out of 143 fishing households in the sample own cattle, compared to 23 out of 157 farming households. This is likely due to the fact that these villages often lack grazing commons, so fishing households who typically do not own farmland also lack land for grazing and agricultural residues for livestock feed. Similarly, coefficients for "boat fishing" in the choice models for land-based substitutes like tree lots and agricultural residue are also negative, but not significant at the $P = 0.05$ level, which weakly suggests that fishing households are less likely to utilize these substitutes.

The coefficients for the farming fixed effect are less ambiguous and thus more informative. Significantly positive coefficients strongly indicate that farmers are more likely to use home trees, livestock dung, and other agricultural residues for combustible fuels. Consequently, farmers are significantly less likely to utilize fuelwood markets, just as they are less likely to extract mangrove fuelwood. The same cannot be said for farm laborers, who are significantly more likely to use animal dung but not other substitutes. Since cow dung is often prepared as fuel by encasing it over tree stems, it both complements and substitutes for woody material, and thus has countervailing impacts on fuelwood demand. Thus, the greater use of cow dung among farm laborers does not correspond to significantly different usage of mangrove or purchased fuelwood.

Persons per room is significantly and negatively correlated with the probability of buying fuelwood at market, since poorer households would have less access to cash for making such purchases. Substituting the PCA-derived socioeconomic index for persons per room yields similar results. However, in this case, the coefficient for the socioeconomic index is weakly significant in the probit model for other agricultural residuals, and the farming indicator is also only weakly significant. This result suggests that poorer farmers may be less likely to use agricultural residues as combustible fuel, possibly because they would be producing fewer residues than wealthier, more productive farmers.

6. Conclusions and policy implications

Prior studies of mangrove utilization in South Asia have noted that levels of fuelwood extraction can be quite variable at the household level, but do not attempt to explain this variability (e.g., Gunawardena and Rowan, 2005). The econometric results in this study suggest that determinants of the household decision to collect mangrove fuelwood include respondent occupation and village-level characteristics. Farmers are less likely to extract mangrove fuels due to the availability of substitutes such as home tree lots and livestock dung. Residents of Mirzanagar, where all respondents access non-mangrove fuelwood markets, are also less likely to collect fuelwood from mangroves. Using persons per room as a proxy, this study finds that collection quantities are positively correlated with the degree of impoverishment, and incorporating a PCA-derived socioeconomic index into similar models confirms this result. This outcome accords with other studies in South Asia which report that mangrove utilization for fuelwood is greater among the poorest households (e.g., Baig and Iftikhar, 2007; IUCN, 2007). These results are robust to spatial lag dependence, spatial error dependence, and selection bias, and have important implications for beneficiary selection for future mangrove plantations.

According to the official policy in Bangladesh, beneficiary selection for new plantations will ensure inclusion of poor, vulnerable, and marginalized groups in order to provide short-term employment in afforestation projects (World Bank, 2013). However, in poorer communities, this study suggests that this may result in greater fuelwood extraction, possibly reducing other ecosystem services. Mangroves provide protection by dissipating the huge wave energies that occur during tropical storms. Their dense networks of leaves, trunks, branches, and above-ground roots can create drag forces that reduce wave period and height, while their root structures also help keep soils compact and slow coastal erosion, stabilize intertidal sediments, and promote land accretion (reviewed in Chow, 2017). Thus the extraction of pneumatophores and branches, even while leaving the bole intact, would likely decrease the provision of these ecosystem services.

Therefore, there may be an important trade-off at play when considering the location of future plantations and their intended beneficiaries. Establishing plantations in poorer communities dominated by livelihood activities other than farming would result in greater fuelwood benefits, but potentially also more degradation and fewer protective services. On the other hand, plantations near less poor or predominantly farming communities would likely result in

less fuelwood extraction, leaving the ecosystem more intact to perform other services.

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Appendix

In the Bayesian SAR probit models for the binary collection decision, significance of the spatial correlation coefficient, ρ, indicates the presence of spatial lag dependence, possibly due to the tendency for collectors to harvest fuelwood in groups. Among the SEM models, the spatial correlation coefficient, τ, is also significant for five of six model specifications, which strongly indicates the presence of spatially correlated errors. The signs and significance of the coefficient for the farming and village fixed effects are robust across all specifications (Appendix Table 1).

Appendix Table 1
Parameter estimates for Bayesian spatial dependence probit models regressing fuelwood collection (yes = 1, no = 0) onto explanatory variables (model 9 from Table 4), generated by Gibbs sampling. ρ = correlation coefficient for spatial lag dependence. τ = correlation coefficient for spatial error dependence. *P < 0.10. **P < 0.05. ***P < 0.01. A) SAR model. B) SEM model.

A)

	Probit	Delaunay triangulation	5 nearest neighbors	10 nearest neighbors
Age of respondent	−0.0087 (0.0066)	−0.010 (0.0066)*	−0.0010 (0.0067)*	−0.011 (0.0070)*
Years of education	−0.040 (0.028)	−0.046 (0.029)**	−0.046 (0.030)*	−0.048 (0.029)*
Persons per room	−0.025 (0.075)	−0.050 (0.080)	−0.036 (0.079)	−0.048 (0.080)
Farming	−0.75 (0.20)***	−0.75 (0.21)***	−0.71 (0.20)***	−0.70 (0.21)***
Aladigram	1.00 (0.31)***	0.71 (0.30)**	0.76 (0.31)***	0.71 (0.34)***
Babugonj	1.05 (0.38)***	0.73 (0.02)**	0.63 (0.35)**	0.58 (0.34)**
Mirzanagar	−2.38 (0.34)***	−1.96 (0.35)***	−1.75 (0.33)***	−1.65 (0.36)***
Momripara	0.62 (0.29)**	0.47 (0.28)**	0.40 (0.26)**	0.41 (0.27)*
Constant	1.44 (0.41)***	1.47 (0.43)***	1.38 (0.41)***	1.39 (0.44)***
ρ	NA	0.302 (0.13)**	0.38 (0.11)***	0.40 (0.13)***

B)

	probit	Delaunay triangulation	5 nearest neighbors	10 nearest neighbors
Age of respondent	−0.0087 (0.0066)	−0.0086 (0.0073)	−0.0083 (0.0076)	−0.0092 (0.0079)
Years of education	−0.040 (0.028)	−0.040 (0.033)	−0.035 (0.035)	−0.038 (0.032)
Persons per room	−0.025 (0.075)	−0.037 (0.080)	−0.054 (0.083)	−0.046 (0.084)
Farming	−0.75 (0.20)***	−0.77 (0.22)***	−0.81 (0.24)***	−0.74 (0.23)***
Aladigram	1.00 (0.31)***	1.14 (0.36)***	1.25 (0.41)***	1.34 (0.43)***
Babugonj	1.05 (0.38)***	1.11 (0.36)***	1.06 (0.39)***	1.13 (0.46)**
Mirzanagar	−2.38 (0.34)***	−2.47 (0.41)***	−2.57 (0.45)***	−2.50 (0.48)***
Momripara	0.62 (0.29)**	0.64 (0.34)**	0.60 (0.39)*	0.63 (0.45)*
Constant	1.44 (0.41)***	1.49 (0.47)***	1.59 (0.49)***	1.54 (0.49)***
τ	NA	0.21 (0.12)**	0.34 (0.087)**	0.42 (0.11)***

SAR and SEM models for collection quantities reveal that ρ and τ are not significant for any of the contiguity matrix specifications, which indicate the absence of both spatial lag dependence and spatial error dependence (Appendix Table 2). The coefficient for the fishing labor fixed effect is not significant for any specification that compensates for spatial spillovers. These results suggest that occupation has little or no impact on collection quantities. However, the coefficient for persons per room, the Aladigram/Kalirchar fixed effect, and the Babugonj fixed effect are moderately or strongly significant for all spatial model specifications. This concurrence with the simple OLS model indicates the robustness of these results.

Appendix Table 2
Parameter estimates for SAR model regressing total fuelwood collected (kg) on explanatory variables (specification 8 from Table 7). ρ = correlation coefficient for spatial lag dependence. τ = correlation coefficient for spatial error dependence. *P < 0.10. **P < 0.05. ***P < 0.01. A) SAR model. B) SEM model.

A)

	OLS (robust SE)	Delaunay triangulation	5 nearest neighbors	10 nearest neighbors
Kg per collection time	11 (2.8)***	11.4 (1.9)***	11.1 (1.9)***	11 (1.9)***
Age of respondent	−20.7 (24.5)	−21.3 (21.2)	−20.4 (21.5)	−20.7 (21.5)
Years of education	24.8 (65)	35.1 (96.6)	25.4 (97.8)	24.9 (97.8)
Persons per room	514.4 (213.7)**	561.5 (201.2)***	521.6 (204.2)**	515.4 (204.5)**
Fish labor FE	−1072 (538.7)**	−1142.1 (1048.8)	−1082.8 (1062.6)	−1070.2 (1063.8)
Aladigram FE	2125.4 (941.3)**	2475.8 (714.7)***	2181.2 (724.2)***	2133.1 (740.2)***
Babugonj FE	−2486.7 (518.5)***	−2709.3 (807.3)***	−2528 (824.8)***	−2491.7 (825.1)***
Constant	1324.2 (1069)	1704.3 (1215.6)	1369.3 (1229.1)	1332.2 (1248.5)
ρ	NA	−0.21 (0.11)**	−0.03 (0.1)	0 (0.14)

B)

	OLS (robust SE)	Delaunay triangulation	5 nearest neighbors	10 nearest neighbors
Kg per collection time	11 (2.8)***	10.9 (1.8)***	11 (1.9)***	11 (1.9)***
Age of respondent	−20.7 (24.5)	−19.8 (21.2)	−20.6 (21.5)	−20.7 (21.5)
Years of education	24.8 (65)	20.8 (96.6)	24.8 (97.9)	25.2 (97.6)
Persons per room	514.4 (213.7)**	544 (201.5)**	514.7 (203.4)**	513.2 (203.5)**
Fish labor FE	−1072 (538.7)**	−1211.6 (1015.6)	−1071.7 (1062.2)	−1076.6 (1062.8)
Aladigram FE	2125.4 (941.3)**	2156.3 (608.6)***	2126.1 (702.1)***	2124.3 (708.3)***
Babugonj FE	−2486.7 (518.5)***	−2490.9 (701.1)***	−2486.5 (810.5)***	−2485 (817.4)***
Constant	1324.2 (1069)	1206 (1173.1)	1321.4 (1207.1)	1328.2 (1208.5)
τ	NA	−0.19 (0.12)	0 (0.11)	0.01 (−0.16)

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